MATLAB EXPO 2018
KOREA

MATLAB EXPO 2018

Deploying Deep Learning Networks to Embedded GPUs and CPUs

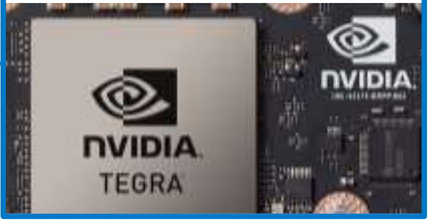
성 호 현 부장

MATLAB Deep Learning Framework

Access Data

Design + Train

Deploy

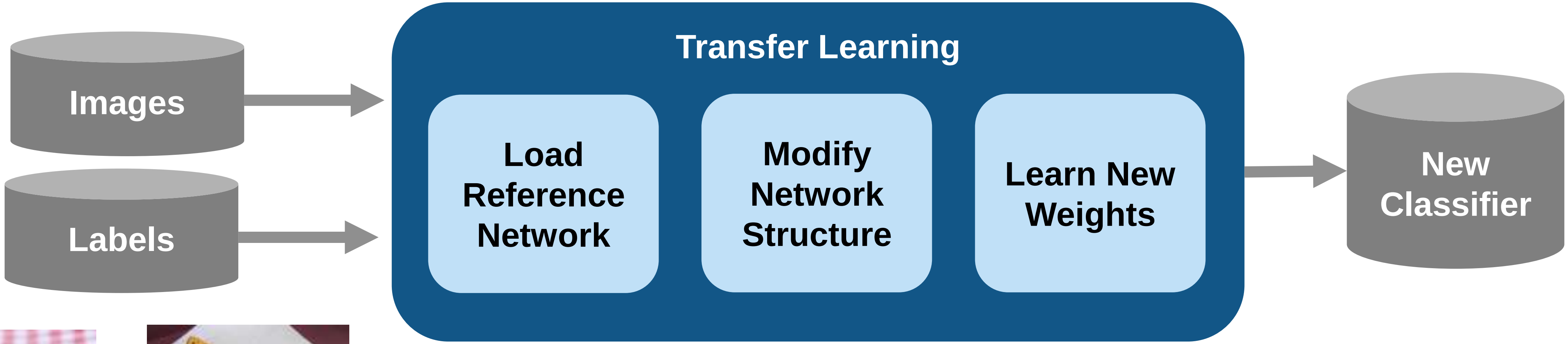


- **Manage** large image sets
- **Automate** image labeling
- **Easy access** to models

- **Acceleration** with GPU’s
- **Scale** to clusters

- **Automate compilation to GPUs and CPUs using GPU Coder:**
  - **5x faster** than TensorFlow
  - **2x faster** than MXNet

Design Deep Learning & Vision Algorithms
Transfer Learning Workflow



Labels: Hot dogs, Pizzas, Ice cream, Chocolate cake, French fries

Training Data

Example: Transfer Learning in MATLAB

Set up training dataset

Load Reference Network

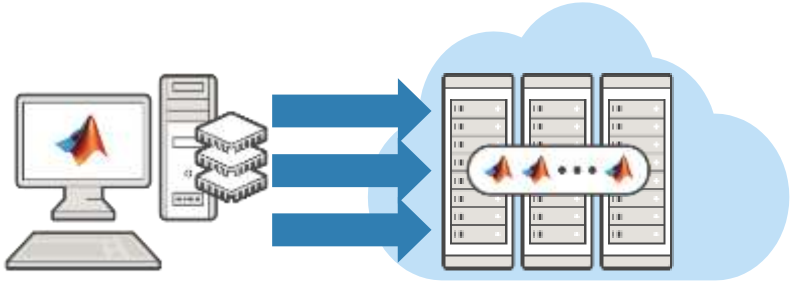
Modify Network Structure

Learn New Weights

```
%% set up training dataset
cifarFolder = 'cifar10Train';
categories = {'Cars', 'Trucks', 'BigTrucks', 'Suvs', 'Vans'};
imds = imageDatastore(fullfile(cifarFolder, categories), ...
    'LabelSource', 'foldernames');

imds = splitEachLabel(imds, 500, 'randomize'); % we only need 500 images per class
imds.ReadFcn = @readFunctionTrain;

%% load reference network
net = alexnet;
layers = net.Layers;

%% modify network
layers = layers(1:end-3);

layers(end+1) = fullyConnectedLayer(64, 'Name', 'special_2');
layers(end+1) = reluLayer;
layers(end+1) = fullyConnectedLayer(5, 'Name', 'fc8_2 ');
layers(end+1) = softmaxLayer;
layers(end+1) = classificationLayer();

%% train!
options = trainingOptions('sgdm', ...
    'LearnRateSchedule', 'none',...
    'InitialLearnRate', .0001,...
    'MaxEpochs', 20, ...
    'MiniBatchSize', 128);

myConvnet = trainNetwork(imds, layers, options);
```

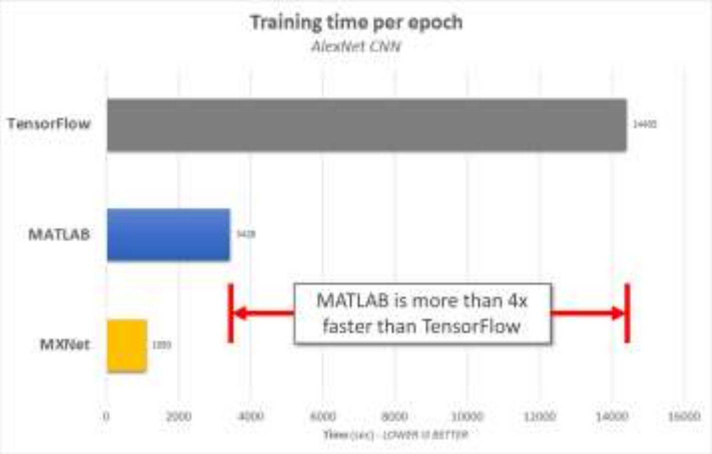
Scaling Up Model Training Performance

```
'ExecutionEnvironment', 'parallel' );
```

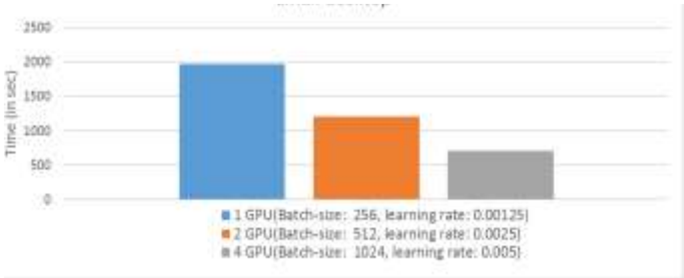


Training on the AWS (EC2)

```
opts = trainingOptions('sgdm', ...
    'MaxEpochs', 100, ...
    'MiniBatchSize', 250, ...
    'InitialLearnRate', 0.00005, ...
    'ExecutionEnvironment', 'auto' );
```




```
'ExecutionEnvironment', 'multi-gpu' );
```

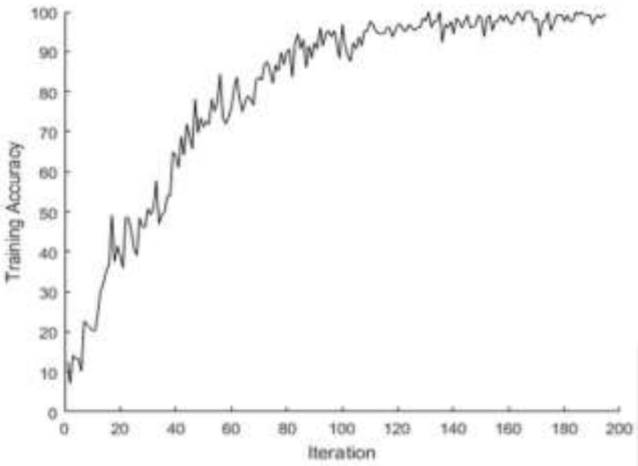


Multiple GPU support

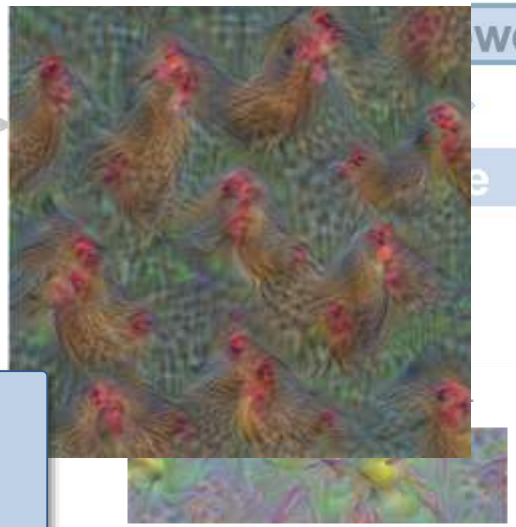
Single GPU performance

Visualizing and Debugging Intermediate Results

Training Accuracy Visualization



Deep Dream



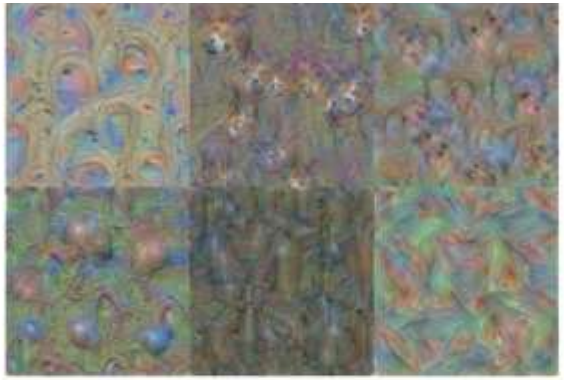
- Many options for visualizations and debugging
- Examples to get started

Filters

Layer Activations

Activations

Feature Visualization



GPU Coder for Deployment

MATLAB

GPU Coder

Accelerated implementation of parallel algorithms on GPUs & CPUs

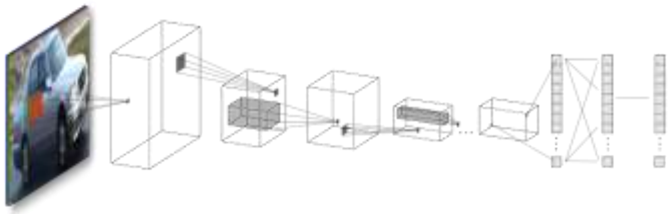
Intel MKL-DNN Library

NVIDIA CUDA C/C++

ARM Compute Library

Deep Neural Networks

Deep Learning, machine learning



5x faster than TensorFlow
2x faster than MXNet

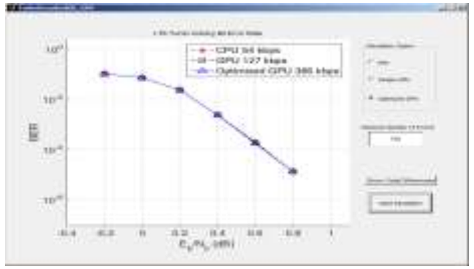
Image Processing and Computer Vision

Image filtering, feature detection/extraction

60x faster than CPUs for stereo disparity

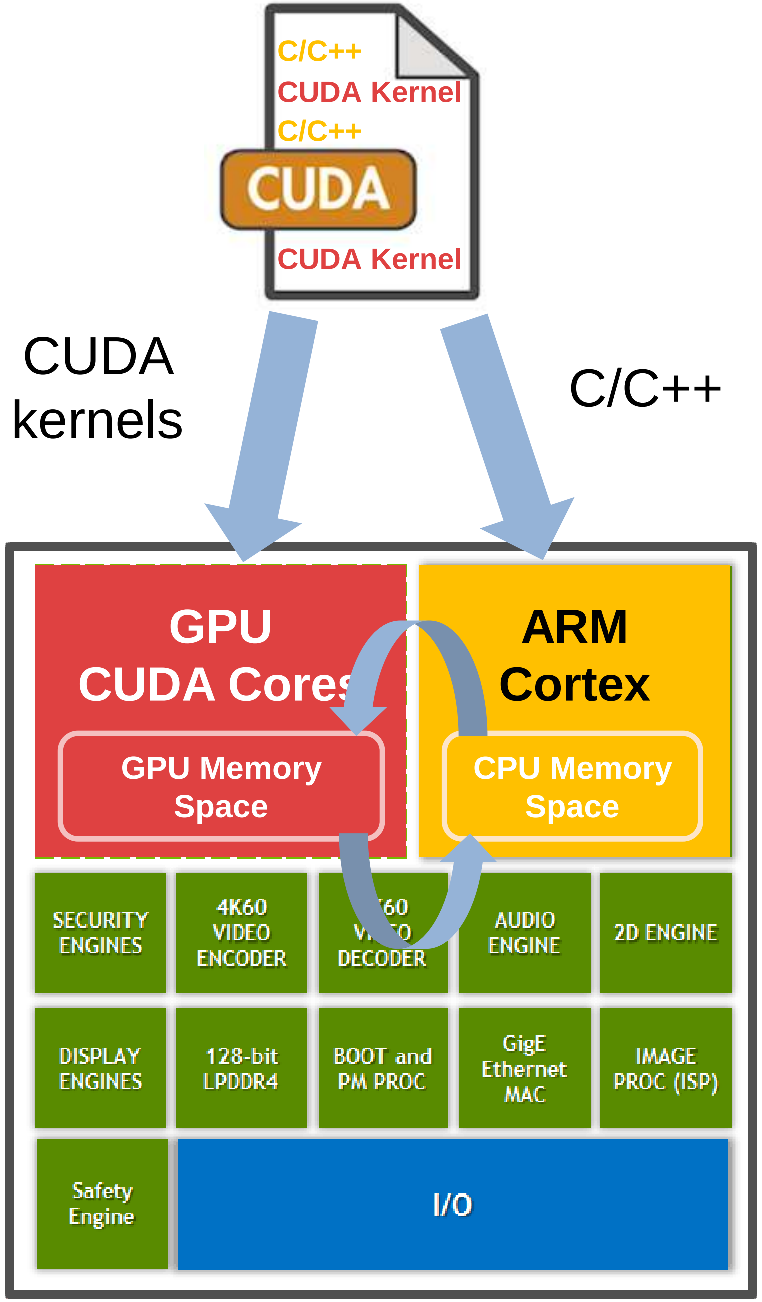
Signal Processing and Communications

FFT, filtering, cross correlation,



20x faster than CPUs for FFTs

GPUs and CUDA



Challenges of Programming in CUDA for GPUs

- Learning to program in CUDA
  - Need to rewrite algorithms for parallel processing paradigm
- Creating CUDA kernels
  - Need to analyze algorithms to create CUDA kernels that maximize parallel processing
- Allocating memory
  - Need to deal with memory allocation on both CPU and GPU memory spaces
- Minimizing data transfers
  - Need to minimize while ensuring required data transfers are done at the appropriate parts of your algorithm

GPU Coder Helps You Deploy to GPUs Faster

MATLAB

GPU Coder

- CUDA Kernel creation
- Memory allocation
- Data transfer minimization

NVIDIA CUDA C/C++

- Library function mapping
- Loop optimizations
- Dependence analysis

- Data locality analysis
- GPU memory allocation

- Data-dependence analysis
- Dynamic memcpy reduction

GPU Coder Generates CUDA from MATLAB: saxpy

Scalarized MATLAB

```
for i = 1:length(x)
    z(i) = a .* x(i) + y(i);
end
```

GPU Coder

Vectorized MATLAB

```
z = a .* x + y;
```

CUDA

```
cudaMalloc(&gpu_z, 8388608UL);
cudaMalloc(&gpu_x, 4194304UL);
cudaMalloc(&gpu_y, 4194304UL);
cudaMemcpy((void *)gpu_y, (void *)y, 4194304UL, cudaMemcpyHostToDevice);
cudaMemcpy((void *)gpu_x, (void *)x, 4194304UL, cudaMemcpyHostToDevice);
saxpy_kernel1<<<dim3(2048U, 1U, 1U), dim3(512U, 1U, 1U)>>>(gpu_y, gpu_x, a,
  gpu_z);
cudaMemcpy((void *)z, (void *)gpu_z, 8388608UL, cudaMemcpyDeviceToHost);
cudaFree(gpu_y);
cudaFree(gpu_x);
cudaFree(gpu_z);
```

CUDA kernel for GPU parallelization

```
static __global__ __launch_bounds__(512, 1) void saxpy_kernel1(const real32_T *y,
  const real32_T *x, real32_T a, real_T *z)
{
  int32_T i;

  i = (int32_T)(((((gridDim.x * gridDim.y * blockIdx.z + gridDim.x * blockIdx.y)
                  + blockIdx.x) * (blockDim.x * blockDim.y * blockDim.z) +
                 threadIdx.z * blockDim.x * blockDim.y) + threadIdx.y *
                blockDim.x) + threadIdx.x);
  if (!(i >= 1048576)) {
    z[i] = (real_T)(a * x[i] + y[i]);
  }
}
```

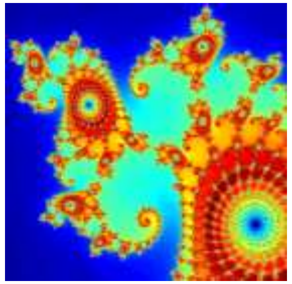
Loops and matrix operations are directly compiled into kernels

Generated CUDA Optimized for Memory Performance

Kernel data allocation is automatically optimized

```
z = z0;
for n = 0:maxIterations
    z = z.*z + z0;
    inside = abs( z )<=2;
    count = count + inside;
end
count = log( count );
```

GPU Coder



Mandelbrot space

CUDA kernel for GPU parallelization

```
static __global__ __launch_bounds__(512, 1) void kernel3(creal_T *z0, real_T
  *count, creal_T *z)
{
  real_T z_im;
  real_T y[1000000];
  int32_T threadIdX;
  threadIdX = (int32_T)(blockDim.x * blockIdx.x + threadIdx.x);
  if (!(threadIdX >= 1000000)) {
    z_im = z[threadIdX].re * z[threadIdX].im + z[threadIdX].im * z[threadIdX].re;
    z[threadIdX].re = (z[threadIdX].re * z[threadIdX].re - z[threadIdX].im *
                       z[threadIdX].im) + z0[threadIdX].re;
    z[threadIdX].im = z_im + z0[threadIdX].im;
    y[threadIdX] = hypot(z[threadIdX].re, z[threadIdX].im);
    count[threadIdX] += (real_T)(y[threadIdX] <= 2.0);
  }
}
```

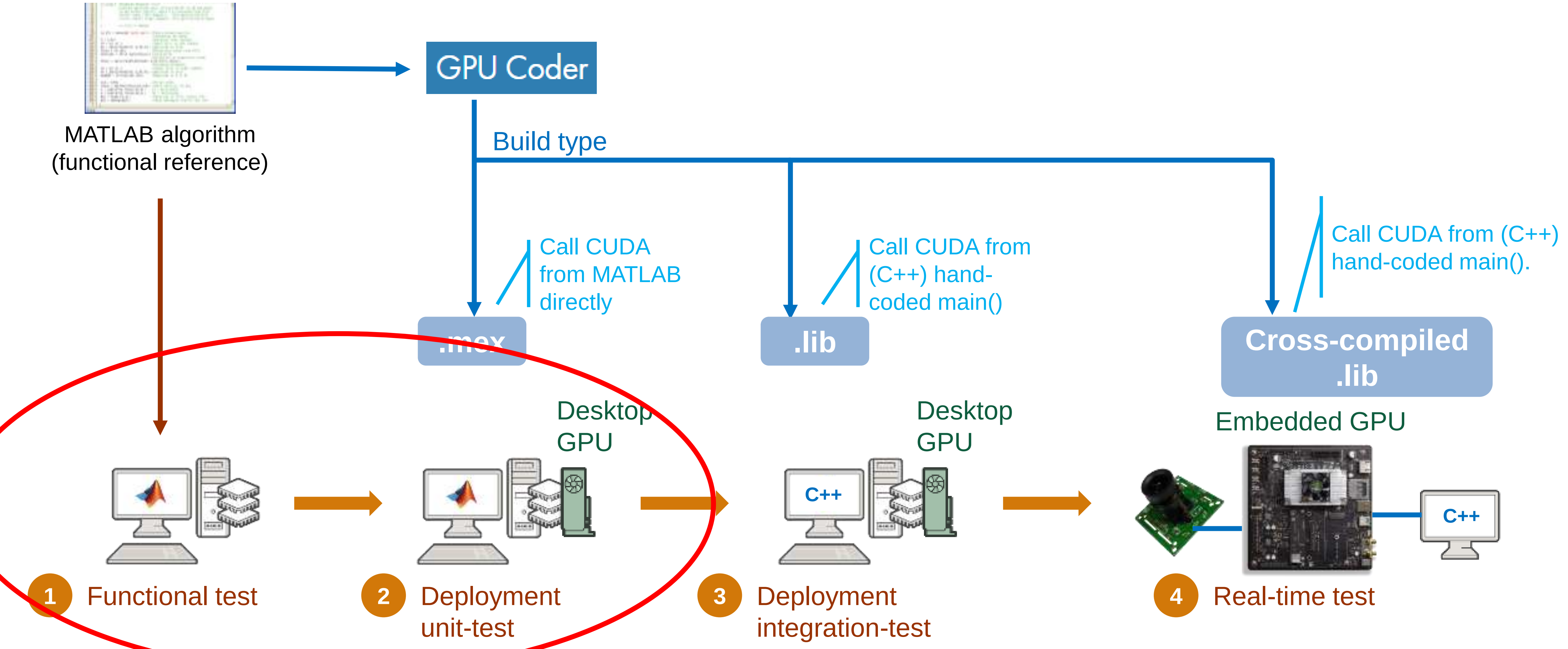
CUDA

…
…

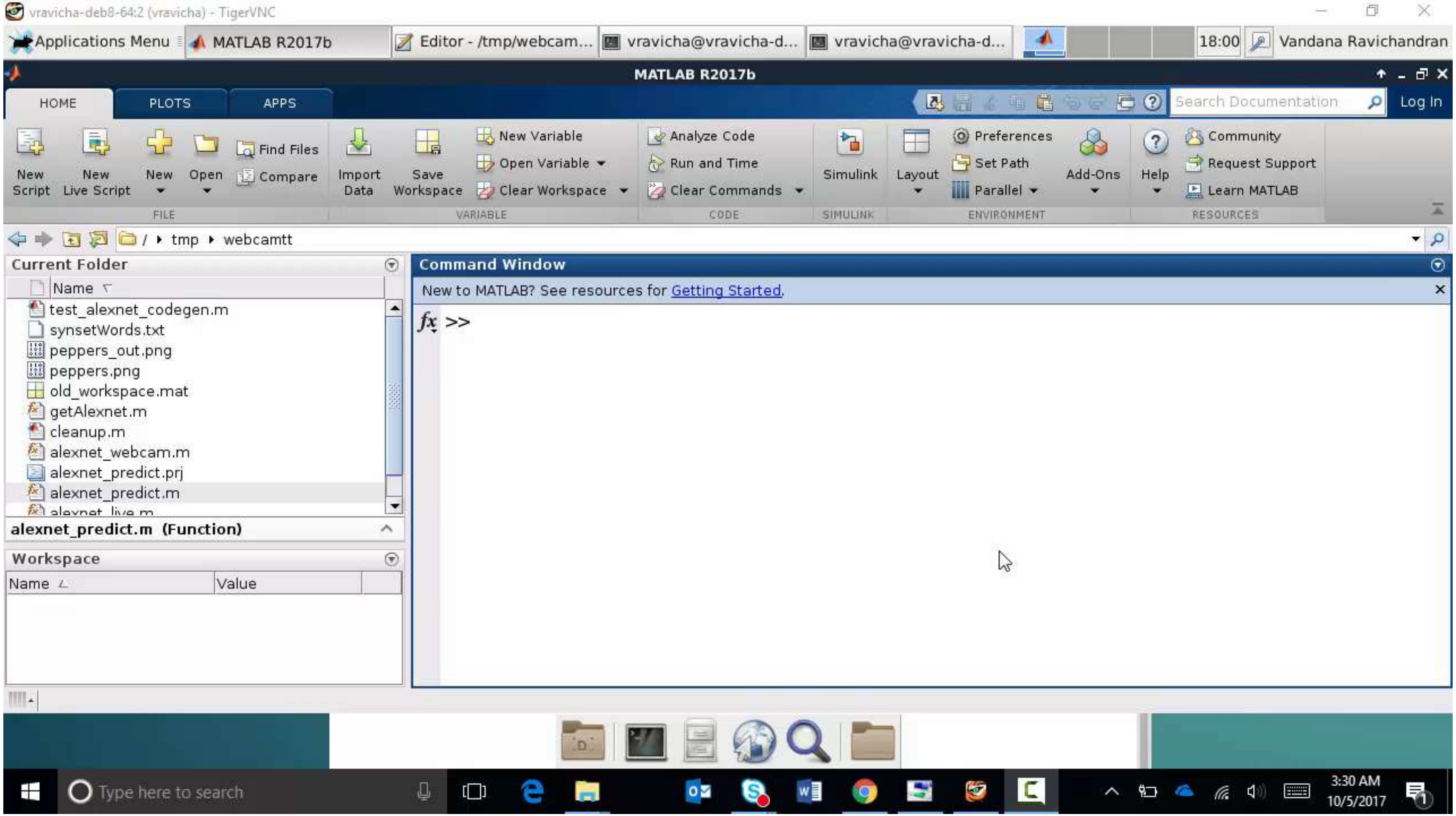
```
cudaMalloc(&gpu_xGrid, 8000000U);
cudaMalloc(&gpu_yGrid, 8000000U);

/*  mandelbrot computation */
cudaMemcpy(gpu_yGrid, yGrid, 8000000U, cudaMemcpyHostToDevice);
cudaMemcpy(gpu_xGrid, xGrid, 8000000U, cudaMemcpyHostToDevice);
kernel1<<<dim3(1954U, 1U, 1U), dim3(512U, 1U, 1U)>>>(gpu_yGrid, gpu_xGrid,
  gpu_z, gpu_count, gpu_z0);
for (n = 0; n < (int32_T)(maxIterations + 1.0); n++) {
  kernel3<<<dim3(1954U, 1U, 1U), dim3(512U, 1U, 1U)>>>(gpu_z0, gpu_count,
    gpu_z);
}

kernel2<<<dim3(1954U, 1U, 1U), dim3(512U, 1U, 1U)>>>(gpu_count);
cudaMemcpy(count, gpu_count, 8000000U, cudaMemcpyDeviceToHost);
cudaFree(gpu_yGrid);
```

…
…

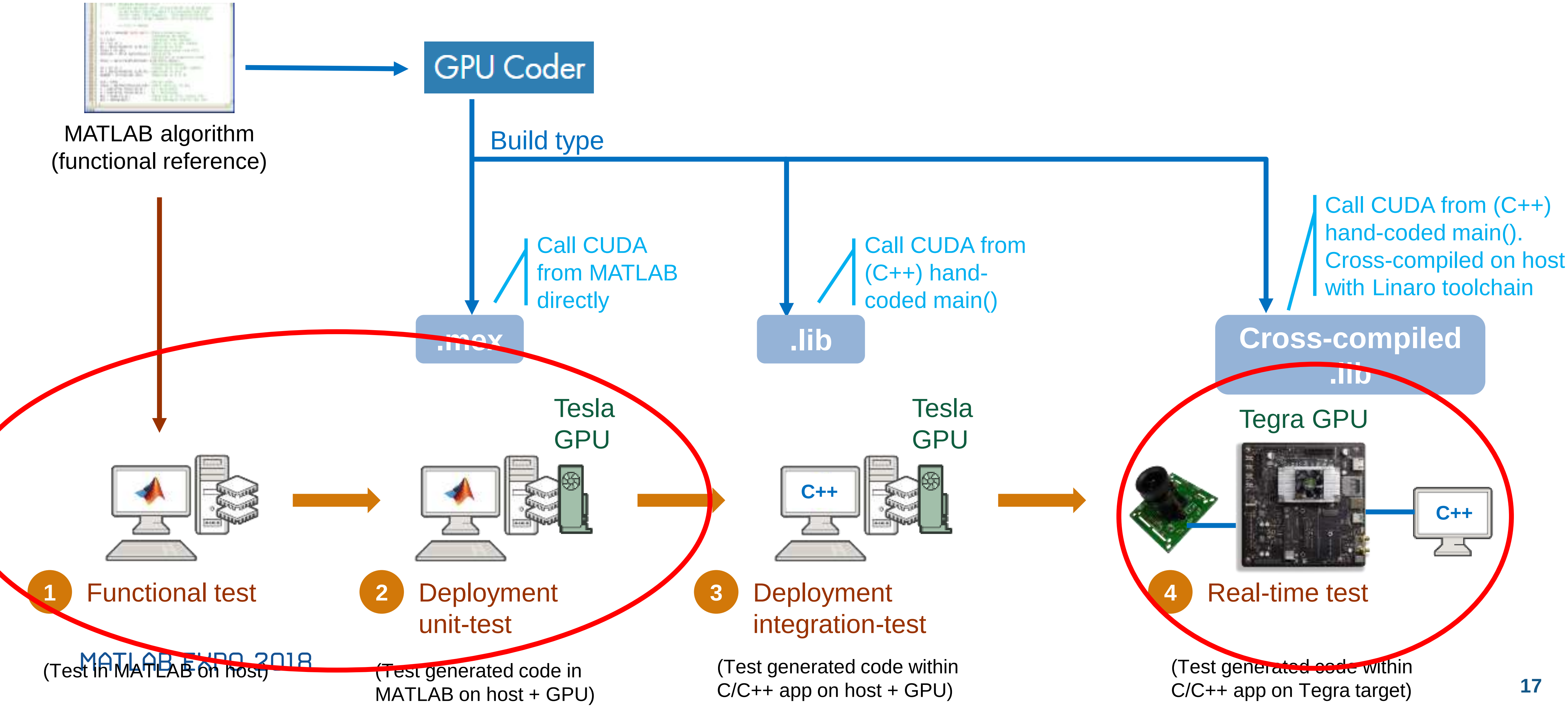
Algorithm Design to Embedded Deployment Workflow



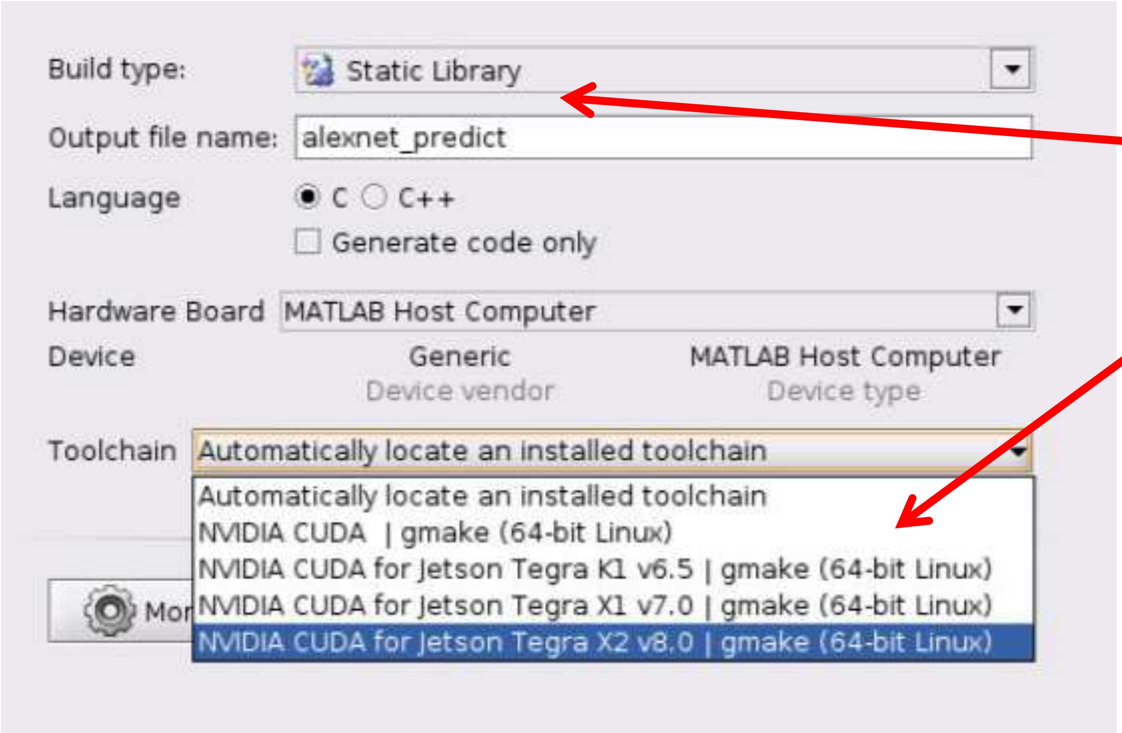
Demo: Alexnet Deployment with ‘mex’ Code Generation



Algorithm Design to Embedded Deployment on Tegra GPU

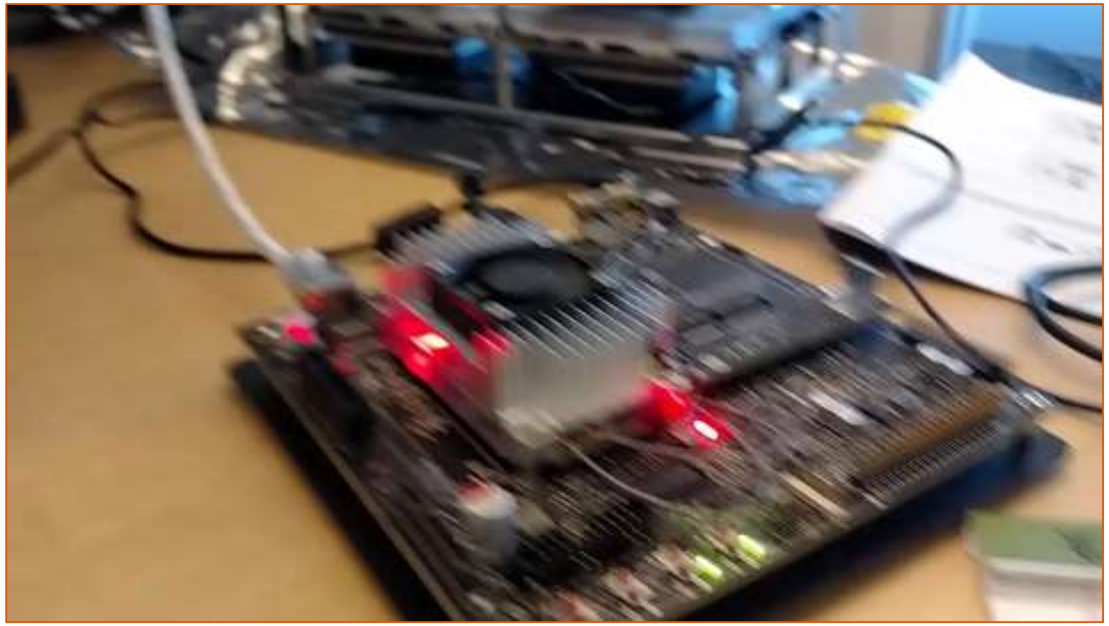


Alexnet Deployment to Tegra: Cross-Compiled with 'lib'



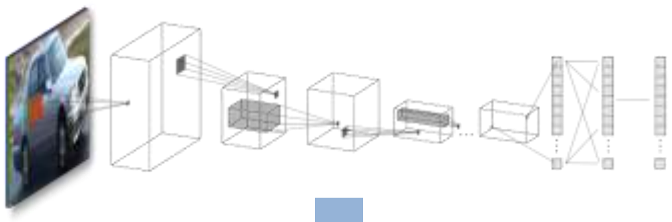
<u>Two small changes</u>

1. Change build-type to 'lib'
2. Select cross-compile toolchain



End-to-End Application: Lane Detection

Alexnet



Transfer Learning

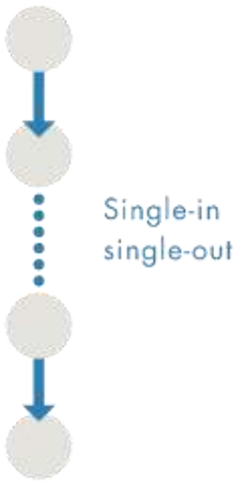
Output of CNN is lane parabola coefficients according to: $y = ax^2 + bx + c$

Image → **Lane detection CNN** → Left lane coefficients / Right lane coefficients → **Post-processing (find left/right lane points)** → Image with marked lanes

GPU coder generates code for whole application

Deep Learning Network Support (with Neural Network Toolbox)

SeriesNetwork



GPU Coder: **R**2017**b**

Networks:

- MNist
- Alexnet
- YOLO
- VGG
- Lane detection
- Pedestrian detection

DAGNetwork

GPU Coder: **R**2018**a**

Networks:

- GoogLeNet
- ResNet
- SegNet
- DeconvNet

GoogLeNet, ResNet: Object detection

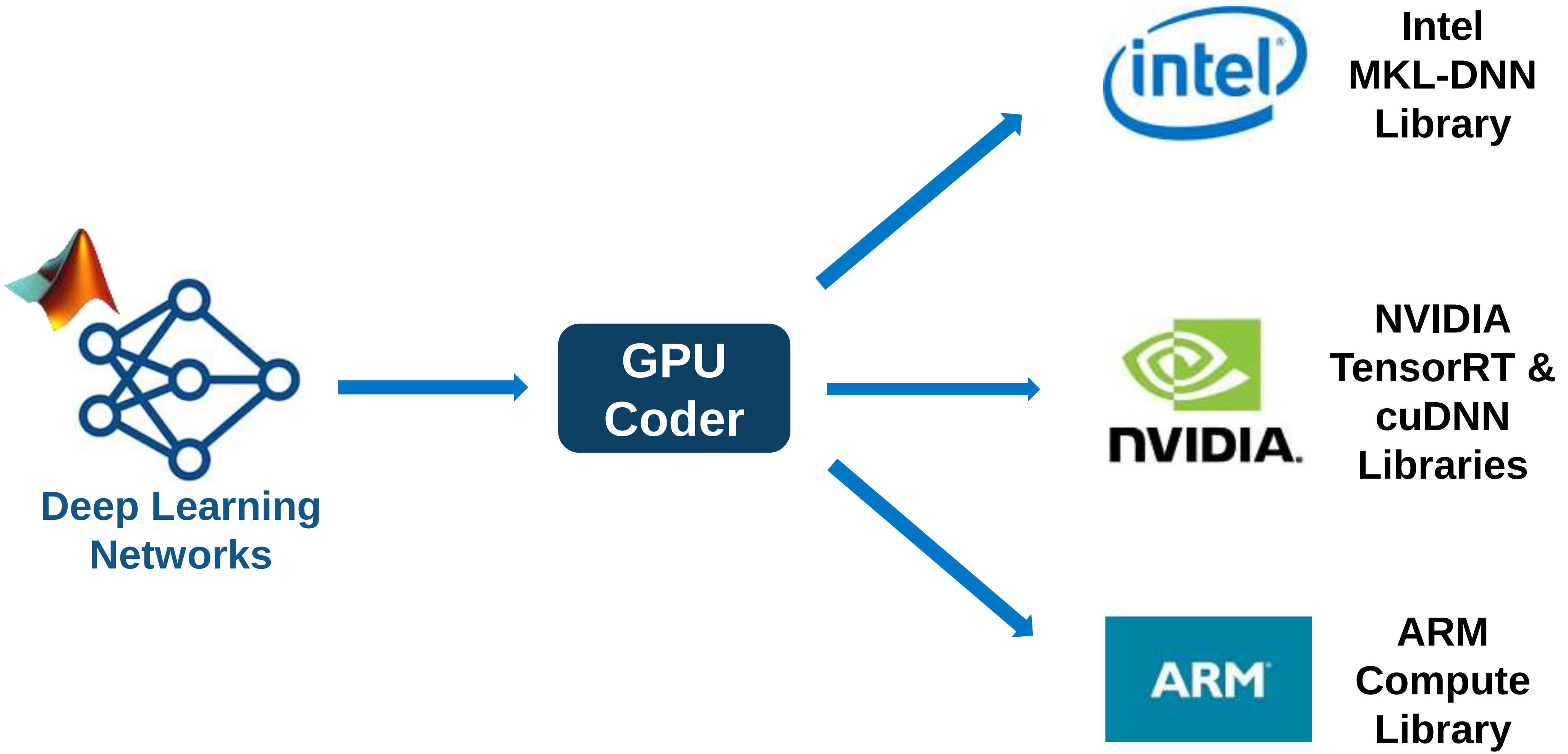
SegNet, DeconvNet: Semantic segmentation

Semantic Segmentation

Running in MATLAB

Generated Code from GPU Coder

Deploying to CPUs



Deploying to CPUs

Deep Learning Networks

GPU Coder

Desktop CPU

NVIDIA TensorRT & cuDNN Libraries

Raspberry Pi board

How Good is Generated Code Performance

- Performance of image processing and computer vision
- Performance of CNN inference (Alexnet) on Titan XP GPU
- Performance of CNN inference (Alexnet) on Jetson (Tegra) TX2

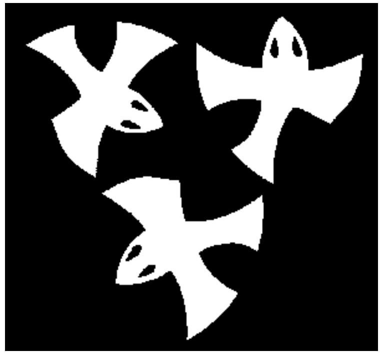
GPU Coder for Image Processing and Computer Vision

Fog removal

5x speedup

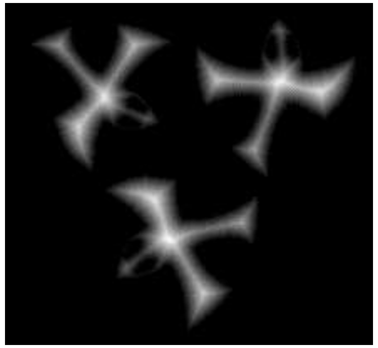
Frangi filter

3x speedup



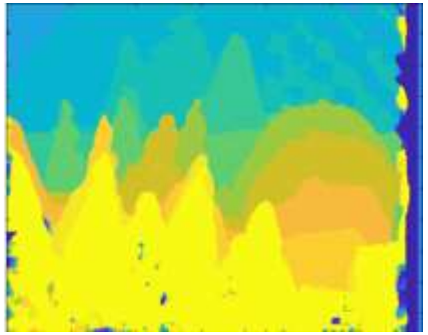
Distance transform

8x speedup



Stereo disparity

50x speedup



Ray tracing

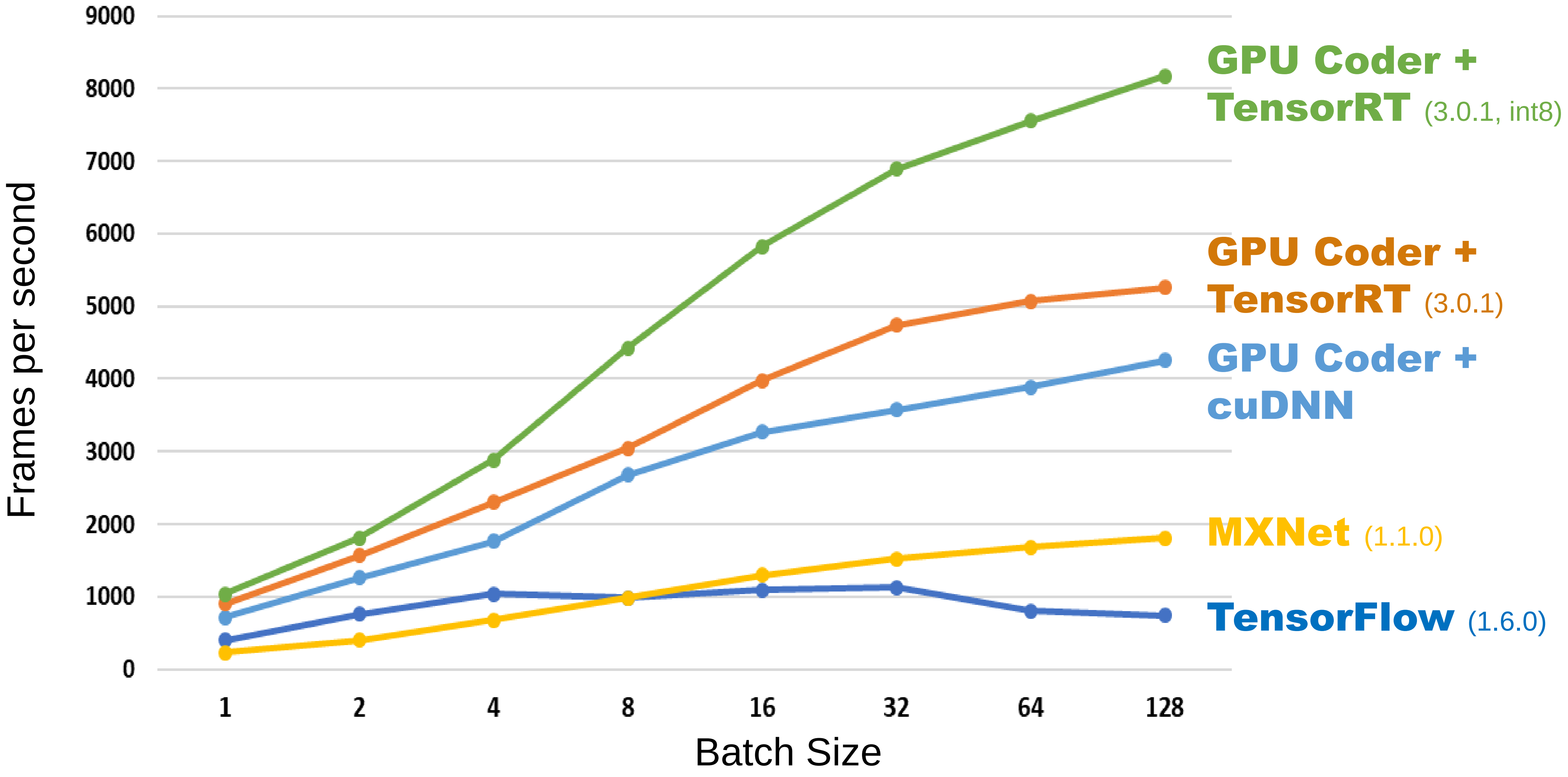
18x speedup

018

SURF feature extraction

700x speedup

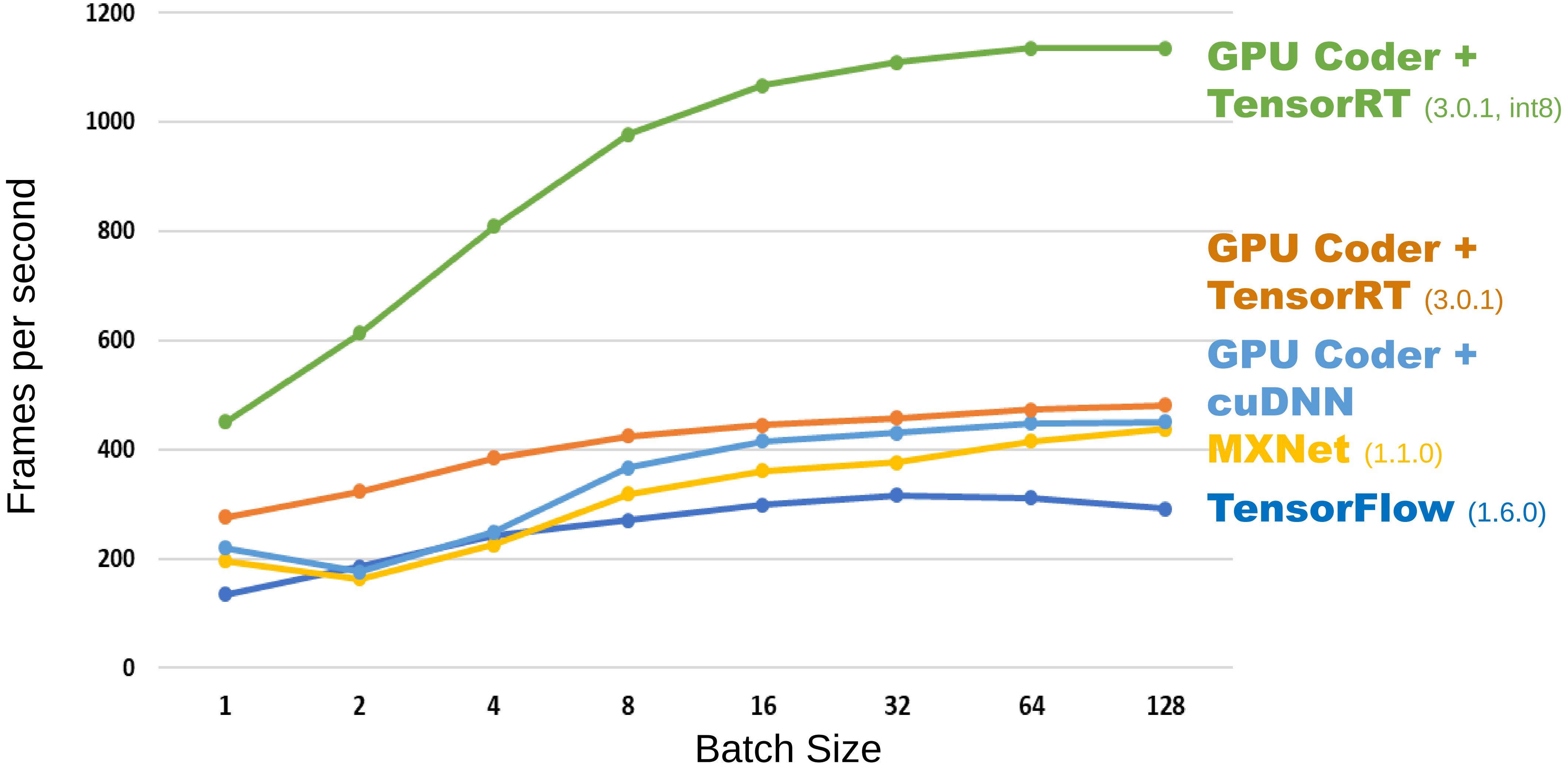
Alexnet Inference on NVIDIA Titan Xp



Testing platform

CPU	Intel(R) Xeon(R) CPU E5-1650 v4 @ 3.60GHz
GPU	Pascal Titan Xp
cuDNN	v7

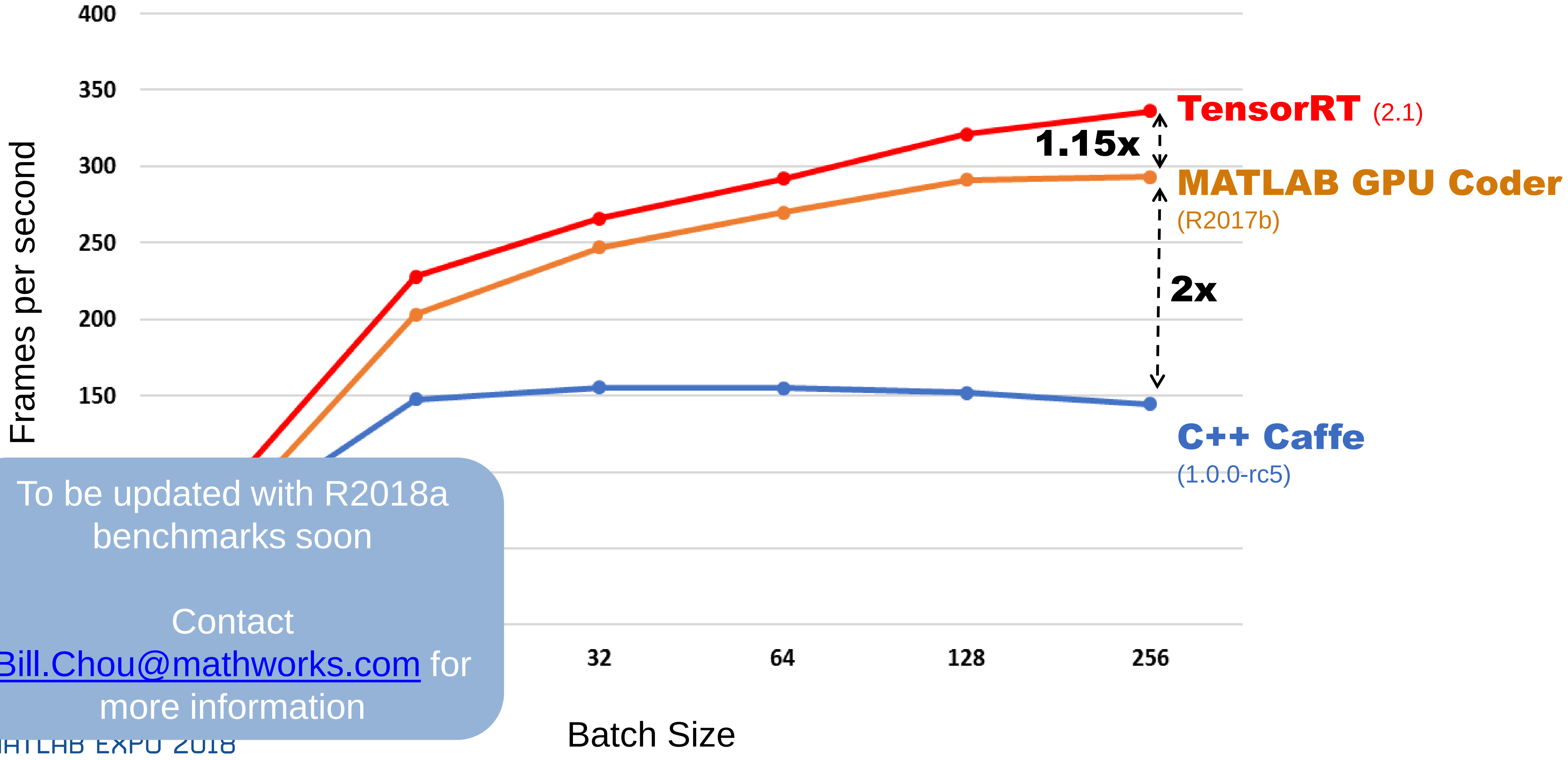
VGG-16 Inference on NVIDIA Titan Xp



Testing platform

CPU	Intel(R) Xeon(R) CPU E5-1650 v4 @ 3.60GHz
GPU	Pascal Titan Xp
cuDNN	v7

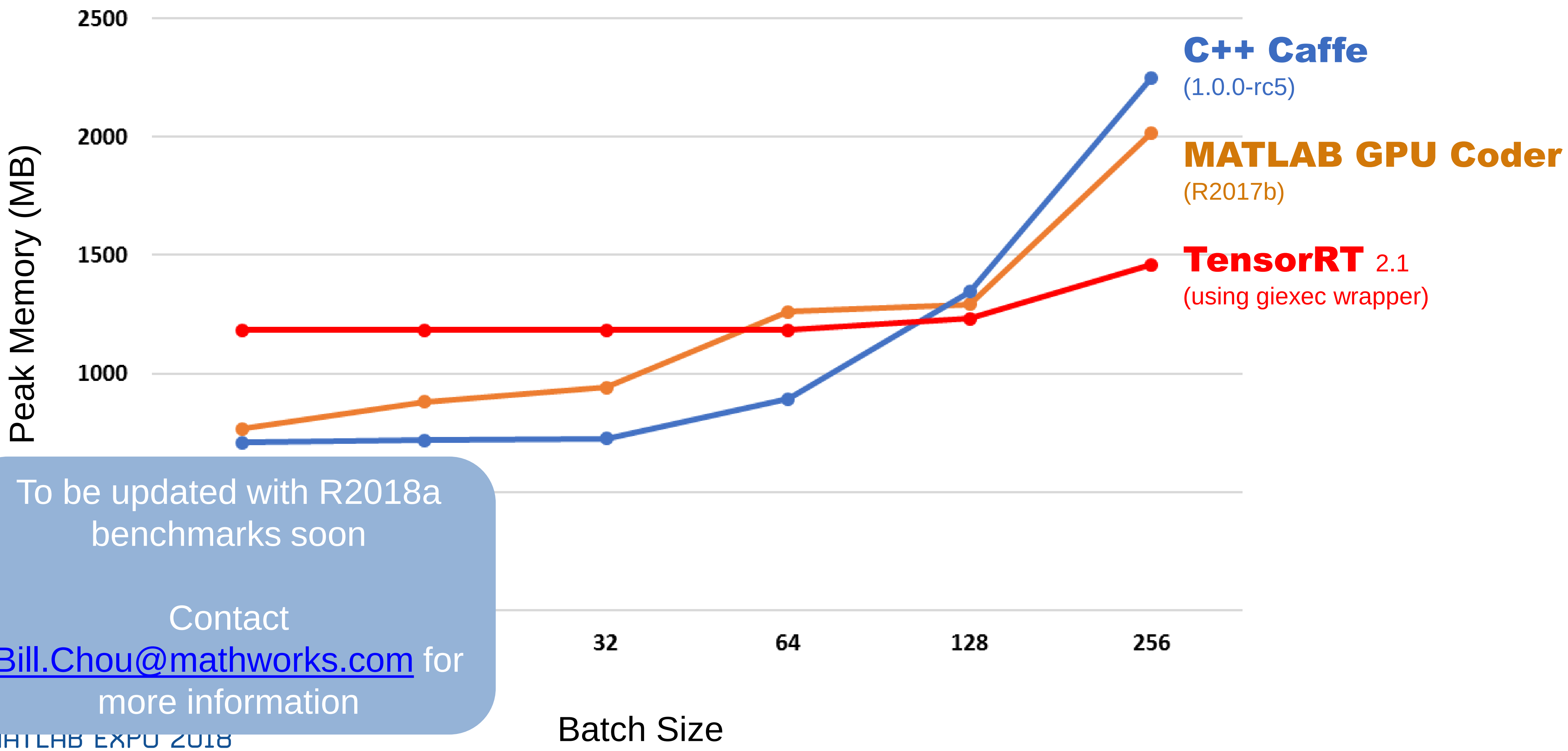
Alexnet Inference on Jetson TX2: Frame-Rate Performance



To be updated with R2018a benchmarks soon

Contact Bill.Chou@mathworks.com for more information

Alexnet Inference on Jetson TX2: Memory Performance



To be updated with R2018a benchmarks soon

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Design Your DNNs in MATLAB, Deploy with GPU Coder

Access Data

Design + Train

Deploy

- **Manage** large image sets
- **Automate** image labeling
- **Easy access** to models

- **Acceleration** with GPU's
- **Scale** to clusters

- **Automate compilation to GPUs and CPUs using GPU Coder:**
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감사합니다.